

Let

- f_θ be a language model.
- T be the tokenizer associated with f_θ .
- $T(w)$ denote the sequence of token IDs of a word w .
- $T(s)$ denote the sequence of token IDs of a sentence s .
- $\text{logsoftmax}(\mathbf{z})$ denote the vector of log-probabilities over the vocabulary obtained from logits \mathbf{z} .
- $\text{LogSumExp}(a_1, \dots, a_K)$ denote $\log\left(\sum_{k=1}^K e^{a_k}\right)$.

Algorithm 1 , dynamic case

Require: sentence s , model f_θ , tokenizer T , set of words \mathcal{W} **Ensure:** mapping Result : $\mathcal{W} \rightarrow \mathbb{R}$ of average log-probabilities

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1:  $x \leftarrow T(s)$   $\triangleright x = (x_1, \dots, x_n)$ , sentence token IDs
2:  $n \leftarrow |x|$   $\triangleright$  number of tokens in the sentence
3: Result  $\leftarrow \emptyset$ 
4: for each word  $w \in \mathcal{W}$  do
5:    $\tau(w) \leftarrow T(w)$   $\triangleright \tau(w) = (t_1, \dots, t_L)$ , token IDs of  $w$ 
6:   if  $|\tau(w)| = 0$  then
7:     Result[ $w$ ]  $\leftarrow \text{NaN}$ 
8:     continue to next  $w$ 
9:    $\mathcal{S} \leftarrow \emptyset$   $\triangleright$  list of joint log-probabilities for each insertion position
10:   $K \leftarrow n + 1$   $\triangleright$  number of insertion positions
11:  for  $k = 0$  to  $n$  do
12:    prefix  $\leftarrow (x_1, \dots, x_k)$ 
13:    context  $\leftarrow$  prefix
14:     $\ell_{\text{joint}} \leftarrow 0$   $\triangleright$  joint log-probability for this insertion position
15:    for  $j = 1$  to  $L$  do
16:      if  $|\text{context}| = 0$  then
17:        eval_context  $\leftarrow (\text{BOS})$   $\triangleright$  BOS token ID from tokenizer
18:      else
19:        eval_context  $\leftarrow$  context
20:         $\mathbf{z} \leftarrow f_\theta(\text{eval\_context})$   $\triangleright$  logits for next token
21:         $\ell \leftarrow \log \text{softmax}(\mathbf{z}_{\text{last}})$ 
22:         $\ell_{\text{token}} \leftarrow \ell[t_j]$ 
23:         $\ell_{\text{joint}} \leftarrow \ell_{\text{joint}} + \ell_{\text{token}}$ 
24:        context  $\leftarrow \text{context} \parallel t_j$   $\triangleright$  append  $t_j$  to context
25:      append  $\ell_{\text{joint}}$  to  $\mathcal{S}$ 
26:    if  $|\mathcal{S}| > 0$  then
27:       $\ell_{\text{sum}} \leftarrow \text{LogSumExp}(\mathcal{S})$ 
28:       $\ell_{\text{avg}} \leftarrow \ell_{\text{sum}} - \log K$ 
29:      Result[ $w$ ]  $\leftarrow \ell_{\text{avg}}$ 
30:    else
31:      Result[ $w$ ]  $\leftarrow \text{NaN}$ 
32: return Result
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Algorithm 2, static case

Require: sentence s , model f_θ , tokenizer T , set of words \mathcal{W}

Ensure: mapping Result : $\mathcal{W} \rightarrow \mathbb{R}$ of average log-probabilities

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1:  $x \leftarrow T(s)$   $\triangleright x = (x_1, \dots, x_n)$ , sentence token IDs
2:  $n \leftarrow |x|$ 
3:  $\mathbf{Z} \leftarrow f_\theta(x)$   $\triangleright \mathbf{Z} \in \mathbb{R}^{n \times |\mathcal{V}|}$ , logits over vocabulary  $\mathcal{V}$ 
4:  $\mathbf{L} \leftarrow \text{log softmax}(\mathbf{Z})$  along the vocabulary dimension  $\triangleright \mathbf{L} \in \mathbb{R}^{n \times |\mathcal{V}|}$  is the static log-probability table
5: Result  $\leftarrow \emptyset$ 
6: for each word  $w \in \mathcal{W}$  do
7:    $\tau(w) \leftarrow T(w)$   $\triangleright \tau(w) = (t_1, \dots, t_L)$ , token IDs of  $w$ 
8:    $L_w \leftarrow |\tau(w)|$ 
9:   if  $L_w = 0$  then
10:     Result[ $w$ ]  $\leftarrow \text{NaN}$ 
11:     continue to next  $w$ 
12:    $\mathcal{S} \leftarrow \emptyset$   $\triangleright$  list of pseudo-joint log-probabilities
13:    $K \leftarrow n - L_w + 1$   $\triangleright$  number of sliding-window positions
14:   for  $k = 1$  to  $K$  do
15:      $\ell_{\text{joint}} \leftarrow 0$ 
16:     for  $j = 1$  to  $L_w$  do
17:        $i \leftarrow k + j - 1$   $\triangleright$  sentence position
18:        $\ell_{\text{token}} \leftarrow \mathbf{L}_{i, t_j}$   $\triangleright$  log-probability of  $t_j$  at position  $i$ 
19:        $\ell_{\text{joint}} \leftarrow \ell_{\text{joint}} + \ell_{\text{token}}$ 
20:     append  $\ell_{\text{joint}}$  to  $\mathcal{S}$ 
21:   if  $|\mathcal{S}| > 0$  then
22:      $\ell_{\text{sum}} \leftarrow \text{LogSumExp}(\mathcal{S})$ 
23:      $\ell_{\text{avg}} \leftarrow \ell_{\text{sum}} - \log K$ 
24:     Result[ $w$ ]  $\leftarrow \ell_{\text{avg}}$ 
25:   else
26:     Result[ $w$ ]  $\leftarrow \text{NaN}$ 
27: return Result
```
